The AMES Wholesale Power Market Test Bed: A Computational Laboratory for Research, Teaching, and Training

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***Abstract*—Wholesale power markets around the world are currently undergoing a controversial restructuring of their architecture and rules of operation. Some commentators have argued that restructuring has not produced the intended improvements in market efficiency while at the same time it has complicated efforts to ensure reliability and fairness of operations. This situation suggests the desirability of having publicly available test beds suitable for the objective study of this restructuring process. This study reports on the AMES Wholesale Power Market Test Bed. AMES is an open-source agent-based computational laboratory designed for the systematic study of restructured wholesale power markets operating over AC transmission grids subject to congestion. The AMES traders have learning capabilities permitting them to evolve their trading strategies over time. The potential usefulness of AMES for research, teaching, and training purposes is discussed and illustrated.**

***Index Terms*—Restructured wholesale power markets, Locational marginal pricing (LMP), Agent-based test bed, Multi-agent stochastic reinforcement learning, Dynamic 5-bus test case, AMES Wholesale Power Market Test Bed**

I. Introduction

CORE features of the market design advocated by the U.S. Federal Energy Regulatory Commission (FERC) in an April 2003 white paper [1] are in operation in the midwest (MISO), New England (ISO-NE), New York (NYISO), and the mid-atlantic states (PJM). These core features include: central administration by an independent market operator; a two-settlement system consisting of a bid/offer-based day-ahead market supported by a parallel real-time market to ensure continual balancing of supply and demand for power; and management of transmission grid congestion by means of locational marginal pricing.

One commonly expressed problem for participants in these restructured wholesale power markets is lack of transparency regarding pricing and settlement rules. Due in great part to the complexity of the market design in its various actual implementations, the business practices manuals and other public documents released by market operators are daunting to read and difficult to comprehend. Moreover, in many energy regions (e.g., MISO), data is only posted in partial and masked form with a significant time delay. The result is that many participants are wary regarding the efficiency, reliability, and fairness of the resulting market outcomes. Moreover, outsiders (e.g., university researchers) are hindered from subjecting the design to systematic testing in an open and impartial manner.

In response to this problem, a group of researchers at Iowa State University has been working to develop the AMES Wholesale Power Market Test Bed.[1] Based on business practices manuals for the MISO and ISO-NE, AMES simulates a centrally administered wholesale power market operating through time over an AC transmission grid. Hourly locational marginal prices (LMP) for the day-ahead market are determined via DC optimal power flow based on the demand bids and supply offers of traders with learning capabilities. AMES is being developed and released as open-source software to facilitate an objective understanding of the restructuring process and to promote communication between market stakeholders and university researchers.

The main features of AMES (V2.02) are outlined in section II. General steps for running AMES simulation experiments are outlined in section III. Section IV presents experimental findings for a dynamic 5-bus test case to illustrate AMES research capabilities. Teaching and training capabilities of AMES are discussed in section V.

II. The AMES Test Bed (Version 2.02)

A. Overview

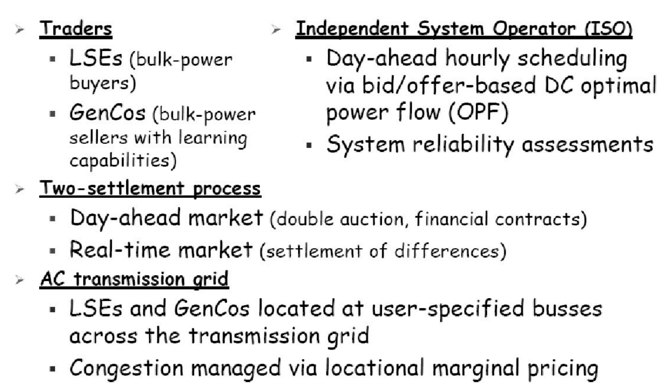

Fig. 1. AMES test bed architecture

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[1] AMES is an acronym for *A*gent-based *M*odeling of *E*lectricity *S*ystems. Downloads, manuals, and tutorial information for all AMES version releases to date can be accessed at the AMES homepage [2].

AMES(V2.02) incorporates, in simplified form, core features of the wholesale power market design proposed by the U.S. FERC [1]; see Figure 1. A detailed description of many of these features can be found in Refs. [3]-[7]. Below is a summary description of the logical flow of events in the AMES wholesale power market as currently implemented:

- The AMES wholesale power market operates over an *AC transmission grid* starting on day 1 and continuing through a user-specified maximum day (unless terminated earlier in accordance with a user-specified stopping rule). Each day D consists of 24 successive hours H = 00,01, ...,23.
- The AMES wholesale power market includes an *Independent System Operator (ISO)* and a collection of energy traders consisting of *Load-Serving Entities (LSEs)* and *Generation Companies (GenCos)* distributed across the busses of the transmission grid. Each of these entities is implemented as a software program encapsulating both methods and data; see, e.g., the schematic depiction of a GenCo in Fig. 2

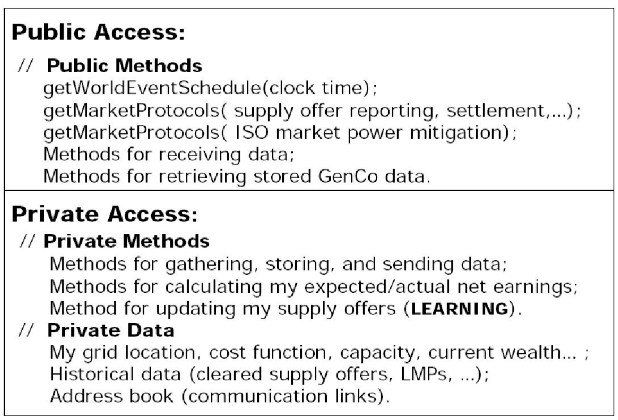

Fig. 2. AMES GenCo: A cognitive agent with learning capabilities

- The objective of the ISO is the reliable attainment of appropriately constrained *operational efficiency* for the wholesale power market, i.e., the maximization of total net benefits subject to generation and transmission constraints.
- In an attempt to attain this objective, the ISO undertakes the daily operation of a *day-ahead market* settled by means of *locational marginal pricing (LMP)*, i.e., the determination of prices for electric power in accordance with both the locating and timing of its injection into, or withdrawal from, the transmission grid.[2]
- The objective of each LSE is to secure power for its downstream (retail) customers. During the morning of each day D, each LSE reports a demand bid to the ISO for the day-ahead market for day D+1. Each demand bid consists of two parts: a *fixed demand bid* (i.e., a 24-hour load profile); and 24 *price-sensitive demand bids* (one for each hour), each consisting of a linear demand function defined over a purchase capacity interval. LSEs have no learning capabilities; LSE demand bids are user-specified at the beginning of each simulation run.
- The objective of each GenCo is to secure for itself the highest possible net earnings each day. During the morning of each day D, each GenCo i uses its current action choice probabilities to choose a *supply offer* from its action domain AD_i to report to the ISO for use in all 24 hours of the day-ahead market for day D+1.[3] Each supply offer in AD_i consists of a linear marginal cost function defined over an operating capacity interval. GenCo i's ability to vary its choice of a supply offer from AD_i permits it to adjust the ordinate/slope of its reported marginal cost function and/or the upper limit of its reported operating capacity interval in an attempt to increase its daily net earnings.
- After receiving demand bids from LSEs and supply offers from GenCos during the morning of day D, the ISO determines and publicly reports hourly power supply commitments and LMPs for the day-ahead market for day D+1 as the solution to hourly bid/offer-based *DC optimal power flow (DC-OPF)* problems. *Transmission grid congestion* is managed by the inclusion of congestion cost components in LMPs.
- At the end of each day D, the ISO settles all of the commitments for the day-ahead market for day D+1 on the basis of the LMPs for the day-ahead market for day D+1.

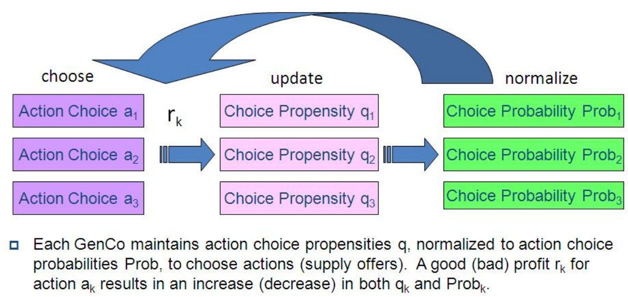

Fig. 3. AMES GenCos use stochastic reinforcement learning to determine the supply offers they report to the ISO for the day-ahead market.

- At the end of each day D, each GenCo i uses *stochastic reinforcement learning* to update the action choice probabilities currently assigned to the supply offers in its action domain AD_i, taking into account its day-D settlement payment ("reward"). In particular, as depicted in Fig. 3, if the supply offer reported by GenCo i on day D results in a relatively good reward, GenCo i increases the probability of choosing this supply offer on day D+1, and conversely.

[2] Roughly stated, a *locational marginal price* at any particular transmission grid bus is the least cost of servicing demand for one additional megawatt (MW) of power at that bus.

[3] In the MISO [8], GenCos each day are actually permitted to report a *separate* supply offer for each hour of the day-ahead market. In order to simplify the learning problem for GenCos, the current version of AMES restricts GenCos to the daily reporting of only one supply offer for the day-ahead market. Interestingly, the latter restriction is imposed on GenCos by the ISO-NE [9] in its particular implementation of FERC's market design. Baldick and Hogan [10, pp. 18-20] conjecture that imposing such limits on the ability of GenCos to report distinct hourly supply offers could reduce their ability to exercise market power.

- There are no system disturbances (e.g., weather changes) or shocks (e.g., forced generation outages or line outages). Consequently, the binding financial contracts determined in the day-ahead market are carried out as planned and traders have no need to engage in real-time (spot) market trading.
- Each LSE and GenCo has an initial holding of money that changes over time as it accumulates earnings and losses.
- There is no entry of traders into, or exit of traders from, the wholesale power market. LSEs and GenCos are currently allowed to go into debt (negative money holdings) without penalty or forced exit.

The activities of the ISO on a typical day D are depicted in Fig. 4. The overall dynamical flow of activities in the wholesale power market on a typical day D in the absence of system disturbances or shocks is depicted in Fig. 5.

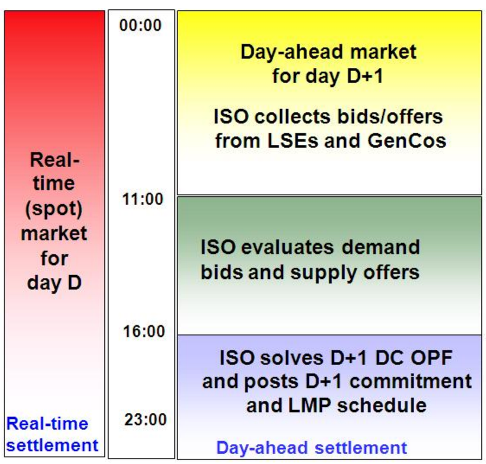

Fig. 4. AMES ISO activities during a typical day D

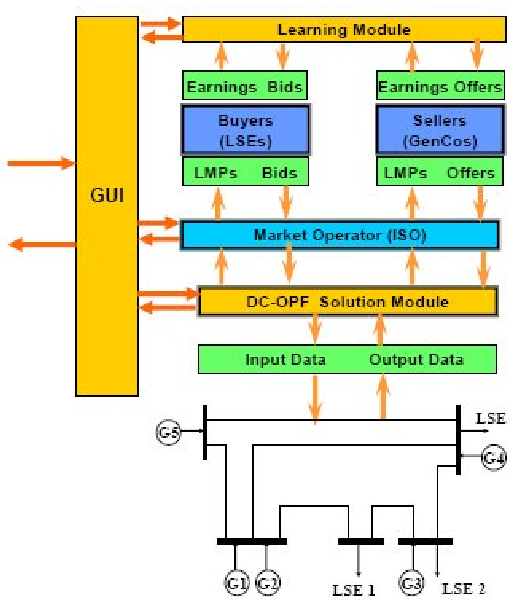

Fig. 5. Illustration of AMES dynamics on a typical day D in the absence of system disturbances or shocks for the special case of a 5-bus grid

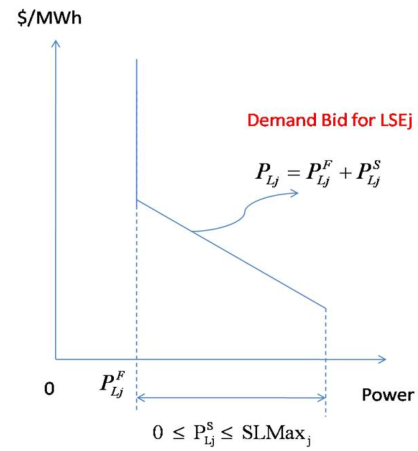

Fig. 6. Illustration of an AMES LSE's fixed and price-sensitive demand bids

B. Demand Bids and Supply Offers

As seen from Fig. 6, for each day D the demand bid reported by LSE j for each hour H of the day-ahead market in day D+1 consists of a *fixed demand bid* p_{Lj}^F(H) (in MWs) and a *price-sensitive demand bid function*

$$D_{jH}(p_{Lj}^S(H)) \;=\; c_j(H) \;-\; 2d_j(H)\cdot p_{Lj}^S(H) \tag{1}$$

defined over a *true purchase capacity interval*

$$0 \;\le\; p_{Lj}^S(H) \;\le\; SLMax_j(H) \tag{2}$$

for real power p_{Lj}^S(H) (in MWs). The expression $D_{jH}(p_{Lj}^S$(H)) denotes LSE j's *true purchase reservation value* for p_{Lj}^S(H), i.e., the maximum dollar amount it is truly willing to pay per MWh for p_{Lj}^S(H).

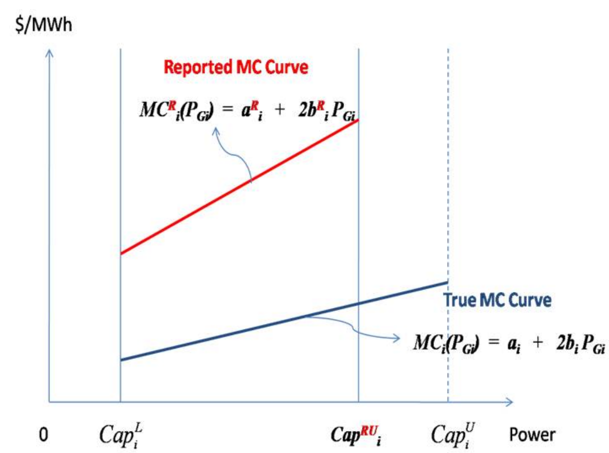

Fig. 7. Illustration of an AMES GenCo's reported marginal cost curve (supply offer) relative to its true marginal cost curve

Also, as seen from Fig. 7, for each day D the single *supply offer* reported by GenCo i for use in each hour H of the day-ahead market for day D+1 consists of a *reported marginal cost function*

$$MC_i^R(p_{Gi}) \;=\; a_i^R \;+\; 2b_i^R\cdot p_{Gi} \tag{3}$$

defined over a *reported operating capacity interval*

$$Cap_i^L \;\le\; p_{Gi} \;\le\; Cap_i^{RU} \tag{4}$$

for real power p_{Gi} (in MWs). The expression $MC_i^R(p_{Gi})$ denotes GenCo i's *reported sale reservation value* for p_{Gi}, i.e., the minimum dollar payment it reports it is willing to accept per MWh for p_{Gi}.

To avoid operating at a point where the true incremental cost of the last supplied MW of power exceeds the marginal benefit (payment) for this last supplied MW of power, GenCo i's reported marginal cost functions always lie on or above its *true marginal cost function*

$$MC_i(p_{Gi}) \;=\; a_i \;+\; 2b_i \cdot p_{Gi} \quad . \tag{5}$$

Also, to avoid infeasible commitments, GenCo i always reports an upper operating capacity level Cap_i^{RU} that lies within GenCo i's *true operating capacity interval*

$$Cap_i^L \;\;\leq\;\; p_{Gi} \;\;\leq\;\; Cap_i^U \quad . \tag{6}$$

Note from the above discussion that each reported supply offer for GenCo i can be summarized in the form of a vector (a_i^R,b_i^R,Cap_i^{RU}).

C. Costs, Profits, and Net Earnings

Total variable cost refers to the costs sustained by a supplier that vary with the level of its operations, whereas *fixed cost* refers to the costs sustained by a supplier independently of its level of operations. *Total cost* refers to the sum of the two.

The *true total variable cost function* for GenCo i for each hour H takes the form

$$TVC_i(p_{Gi}) \;=\; \int_0^{p_{Gi}} MC_i(p)dp \;=\; a_i{\cdot}p_{Gi}{+}b_i{\cdot}[p_{Gi}]^2 \;, \tag{7}$$

and the *true total cost function* for GenCo i for each hour H takes the form

$$TC_i(p_{Gi}) \;=\; [TVC_i(p_{Gi}) + FCost_i] \;\;, \tag{8}$$

where p_{Gi} denotes any real-power generation level in the interval (6). By definition, then, the *fixed cost* for GenCo i in each hour H takes the form

$$TC_i(0) \;=\; FCost_i \;. \tag{9}$$

Profit is defined as revenues minus true total cost. On the other hand, *net earnings* are defined as revenues minus true total *variable* cost. Suppose, in particular, that GenCo i is located at bus $k(i)$ and is committed at a generation level p_{Gi} at price $LMP_{k(i)}$ for hour H of the day-ahead market for day D+1. Then the profit of GenCo i for hour H of day D+1, received at the end of day D, is given by

$$\pi_i(H,D) \;=\; LMP_{k(i)} * p_{Gi} - TC_i(p_{Gi}) \;. \tag{10}$$

On the other hand, the net earnings of GenCo i for hour H of day D+1, received at the end of day D, are given by

$$NE_i(H,D) \;=\; LMP_{k(i)} * p_{Gi} - TVC_i(p_{Gi}) \;. \tag{11}$$

The net earnings of GenCo i over all 24 hours of day D+1, received at the end of day D, are then given by

$$NE_i(D) \;=\; \sum_{H=00}^{H=23} NE_i(H,D) \;. \tag{12}$$

D. Determination of LMPs and Power Commitments

As detailed in [11, Appendix A], the ISO computes hourly LMPs and power commitments for the day-ahead market by solving bid/offer-based DC Optimal Power Flow (OPF) problems that approximate underlying AC-OPF problems. To handle these computations, the ISO makes repeated calls to *DCOPFJ*, an accurate and efficient DC-OPF solver developed by Sun and Tesfatsion [4]. DCOPFJ consists of a strictly convex quadratic programming solver wrapped in an outer SI-pu data conversion shell.

E. GenCo Action Domain Construction

The construction of *action domains* (supply offer choice sets) for the GenCos is a critical modeling issue. Empirical sensibility suggests these action domains should permit flexible choice from among a wide range of possible supply offers, and that the degree of flexibility should be roughly similar across the GenCos. On the other hand, computational practicality suggests the number of supply offers included in each action domain should not be unduly large.

In [11, Appendix B] a brief discussion is given regarding how action domains for the AMES GenCos have been constructed in accordance with these objectives. A rigorous detailed discussion and illustration of action domain construction for the AMES GenCos can be found in [3, Appendix].

F. GenCo Learning

The essential idea of stochastic reinforcement learning is that the probability of choosing an action should be increased (reinforced) if the corresponding reward is relatively good and decreased if the corresponding reward is relatively poor. As detailed in [11, Appendix C], each GenCo determines its supply offers by means of VRE reinforcement learning, a variant of a stochastic reinforcement learning algorithm developed by Alvin Roth and Ido Erev ([12], [13]) on the basis of human-subject experiments. The user can tailor the settings of each GenCo's learning parameter values to its situation, in particular to its cost attributes, its operating capacity, and its anticipated net earnings.

G. Graphical User Interface

AMES has a graphical user interface (GUI) with separate screens for carrying out the following functions: (a) creation, modification, analysis, and storage of case studies; (b) initialization and editing of the structural attributes of the transmission grid; (c) initialization and editing of the structural attributes of LSEs and GenCos; (d) specification of learning parameters for GenCos; (e) specification of simulation controls (e.g., the simulation stopping rule); and (f) customization of table and chart output displays.

H. Simulation Control

The user can control the length of each simulation run by choosing to set (or not) any combination of the following five stopping rules:

- Stop when a specified maximum day is reached.
- Stop when each GenCo is choosing a single supply offer with a probability that exceeds a user-specified threshold probability.
- Stop when the probability distribution used by each GenCo to select its supply offers has stabilized to within a user-specified threshold for a user-specified number of days.
- Stop when the supply offer selected by each GenCo has stabilized to within a user-specified threshold for a user-specified number of days.
- Stop when the net earnings of each GenCo have stabilized to within a user-specified threshold for a user-specified number of days.

When multiple stopping rules are flagged, the simulation run terminates as soon as any one of the flagged stopping rules is satisfied.

III. Running AMES Simulation Experiments

Detailed instructions for developing and running general AMES simulations in either single-run or batch-run mode can be found in the set-up information file included with the AMES software download; see [2]. Here we briefly outline the general sequence of actions for a single simulation run, as follows:

1: To load one of the pre-set test cases (e.g., the 5-Bus Test Case), use the "Case → Load Test Case → 5-Bus Test Case" command sequence on the GUI menu. Alternatively, to create a new case, use the "Case → New Case" command sequence on the GUI menu.

2: For a pre-set test case, either use the default parameter settings (including the default random seed value) or change some or all of these default settings to other admissible values. To change the default parameter settings, or to set parameters for a new case, use the "Case → Case Parameters" command sequence on the GUI menu to access a sequence of setting screens for grid, LSE, GenCo, and simulation control parameters; see, e.g., fig. 8. Inadmissible parameter settings trigger explanatory error messages.

3: To run the case, click the "Start" button on the GUI tool-bar or use the "Command → Start" command sequence from the GUI menu.

4: View a customizable output file in the AMES DATA directory using various programs (e.g., Microsoft Excel, Wordpad).

5: Alternatively, view output data in either table or chart form using either the "View → Output Tables" or the "View → Output Charts" command sequence from the GUI menu.

The AMES GUI tables and charts display six types of output for each run: GenCo commitments; GenCo profits and net earnings; cleared LSE price-sensitive demand; LSE net earnings corresponding to cleared price-sensitive demand; LMPs; and total supply and demand curves. This output is further subdivided into "benchmark" and "learning" portions as follows: (i) initially generated output for a no-learning

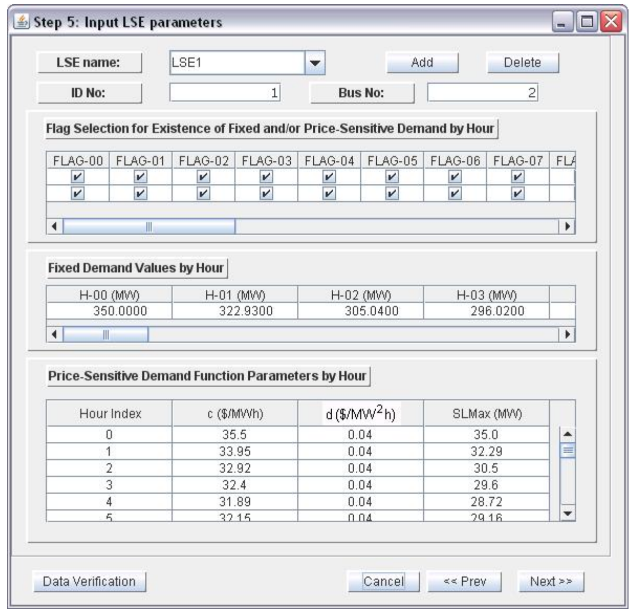

Fig. 8. AMES GUI: Setting screen for LSE fixed demand bids and price-sensitive demand function parameters for each hour

benchmark case in which the supply offers that the GenCos report to the ISO reflect their true cost and capacity attributes; and (ii) subsequently generated output for a *learning case* in which the GenCos attempt to learn over time which supply offers to report to the ISO to increase their net earnings.

As demonstrated in the next section, the benchmark-case output provides a benchmark of comparison for the learning-case output.

IV. AMES Research Capabilities: Illustrative Findings

AMES has been designed with a modular architecture, and released as open source, to encourage the cumulative development of its features and scope. Research applications to date have focused on market performance under alternative learning, demand, and grid specifications; see Refs.[3]-[7].

The AMES download includes dynamic 5-bus and 30-bus test cases to help acquaint users with AMES research capabilities. This section illustrates these capabilities by reporting on experimental findings obtained for 5-bus test case experiments using the AMES default parameter settings.

The configuration of the 5-bus grid for this dynamic 5-bus test case is depicted in Fig. 9. The daily fixed demand (load) profiles for the three LSEs are as shown in Fig. 10. A critical aspect of these profiles is that each peaks at hour 17.[4]

A. Benchmark-Case Results

Fig. 11 displays hourly LMP values for the benchmark dynamic 5-bus test case in which the supply offer of each GenCo consists of its true marginal cost function and its true operating capacity interval. These LMP results illustrate the complicated

[4]The shapes of the fixed demand profiles are adopted from a case study presented in Shahidehpour *et al.* [14, p. 296-297].

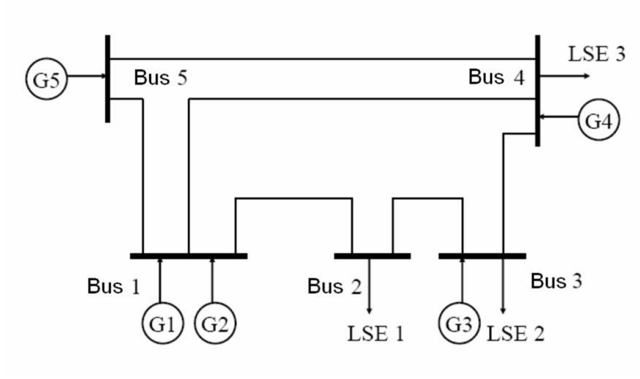

Fig. 9. Transmission grid for the dynamic 5-bus test case

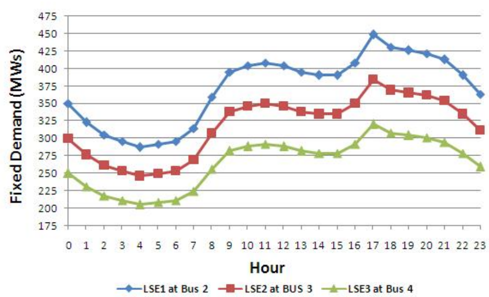

Fig. 10. Daily LSE fixed demand profiles for the dynamic 5-bus test case (all 24 hours, same for each day)

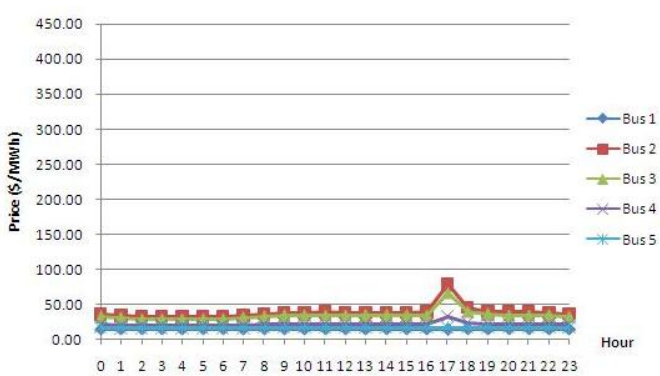

Fig. 11. AMES chart display: Hourly LMPs for the benchmark dynamic 5-bus test case (all 24 hours, same for each day)

influences of daily load profiles, transmission congestion, and operating capacity limits on LMP determination, even in the absence of learning effects.

More precisely, branch congestion occurs between bus 1 and bus 2 (and only these busses) in each of the 24 hours comprising a "typical day" for this benchmark case. The direct consequence of this branch congestion is the occurrence of widespread LMP separation, i.e. the LMP values differ across all busses for each hour. In particular, LMP2 and LMP3 (the LMPs for busses 2 and 3) exhibit a sharp spike around the peak-demand hour 17, increasing by about 100% from hour 16 to hour 17 and then dropping back to more normal levels in hour 18 and beyond.

B. Learning-Case Results

As noted in section II-F, the AMES GenCos are profit-seeking traders who use individual stochastic reinforcement learning to determine which particular supply offers they report to the ISO during each day D for the day-ahead market in day D+1. More precisely, they use their daily net earnings outcomes to update the action choice probilities currently assigned to the supply offers in their admissible action domains, where each supply offer is characterized by a vector (a^R, b^R, cap^{RU}); see Figs. 3 and 7. Direct communication or coordination efforts among the GenCos are not permitted.

In general, the AMES GenCos can engage in both *economic* capacity withholding (choice of a^R and b^R) and *physical* capacity withholding (choice of cap^{RU}). More precisely, the GenCos can report higher-than-true marginal costs and/or less-than-true maximum operating capacities. However, in the particular experiments reported below, the GenCos are restricted to economic capacity withholding only.[5]

Fig. 12 displays the hourly LMP values for all 24 hours of day 51. Comparing Fig. 12 with Fig. 11, the effects of GenCo learning are immediately apparent: the resulting LMP values are *higher* at each bus during off-peak hours and exhibit *more volatility* around the peak-demand hour 17. These correlated LMP effects arise over time solely through the individual profit-seeking actions of the learning GenCos.

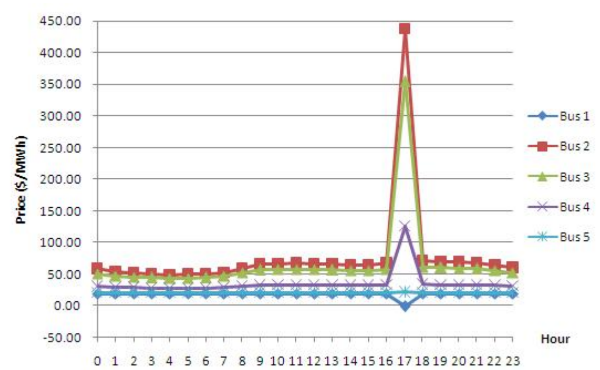

Fig. 12. AMES chart display: Hourly LMPS for the dynamic 5-bus test case with learning (all 24 hours, day 51)

Fig. 13 displays a portion of these same LMP outcomes in table format. The full AMES output table display for LMPs permits users to see precisely how the LMP values change from one day to the next as the learning GenCos adaptively update their supply offer choices. A similar observation holds for the table and figure displays for all types of output. The length of the displays is determined by the user's choice of simulation stopping rule; see section II-H.

Fig. 14 displays the total demand and supply curves for hour 17 of day 51. Note the initial verticality of the total demand curve (corresponding to LSE fixed demand) and the steepness of the remaining portion of the total demand curve (reflecting the relatively small amount of bid-in price-sensitive demand). These demand characteristics are typical for current

[5]See Li et al. [6] for a study permitting the AMES GenCos to engage in both economic and physical capacity withholding.

Bus Name	Day Index	Hour	LMP ($/MWh)
Bus 1	51	16:00	18.54
Bus 2	51	16:00	67.12
Bus 3	51	16:00	57.92
Bus 4	51	16:00	32.60
Bus 5	51	16:00	21.03
Bus 1	51	17:00	-1.04
Bus 2	51	17:00	437.49
Bus 3	51	17:00	354.40
Bus 4	51	17:00	125.91
Bus 5	51	17:00	21.46
Bus 1	51	18:00	18.40
Bus 2	51	18:00	70.56
Bus 3	51	18:00	60.67
Bus 4	51	18:00	33.50
Bus 5	51	18:00	21.07

Fig. 13. AMES table display (only partially shown): Hourly LMPs for the dynamic 5-bus test case with learning (hours 16-18, day 51)

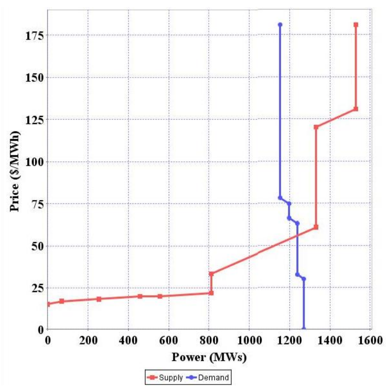

Fig. 14. AMES chart display: Total demand and supply curves calculated from demand bids and supply offers for the dynamic 5-bus test case with learning (hour 17, day 51)

restructured wholesale power markets in the U.S., e.g., the MISO [8].

The intersection of the total demand and supply curves depicted in Fig. 14 occurs at the power-price point (1236.90MW, $55.80/MWh). Note that cleared demand at this point would include both fixed and price-sensitive demand. However, due to congestion on the transmission line between bus 1 and bus 2, only total fixed demand (1153.59MW) is actually cleared; total cleared price-sensitive demand is zero. Moreover, as seen in Fig. 13, this line congestion also causes the LMPs at individual busses to exhibit strong separation. The LMP at bus 1 is -$1.04/MWh, the LMP at bus 2 is $437.49/MWh, the LMP at bus 3 is $354.40/MWh, the LMP at bus 4 is $125.91/MWh, and the LMP at bus 5 is $21.46/MWh. The average of these actual LMP values is $187.64/MWh, far higher than the "market clearing" price level $55.80/MWh depicted in Fig. 14.

Fig. 15 displays daily GenCo profits, net earnings and revenues in table format for two successive days (42 and 43) during which the learning GenCos are still in the process of updating their supply offer choices. Note that the daily net earnings of GenCo 4 actually decline from day 42 to day 43 whereas the the net earnings of the other four GenCos increase. This indicates the extremely complicated multi-agent learning problem faced by the five GenCos; in general, the net earnings attained by any one GenCo during a particular day D depend

GenCo Name	Day Index	Profit ($/D)	Net Earnings ($/D)	Revenues ($/D)
GenCo1	42	83,981.01	85,346.61	123,758.61
GenCo2	42	75,065.19	75,067.83	112,507.83
GenCo3	42	329,720.60	384,141.32	623,568.90
GenCo4	42	79,617.56	79,742.12	180,898.89
GenCo5	42	200,354.16	233,742.00	309,224.76
GenCo1	43	164,505.90	165,871.50	203,620.14
GenCo2	43	150,117.40	150,120.04	187,560.04
GenCo3	43	647,532.63	701,953.35	1,002,976.97
GenCo4	43	47,805.93	47,930.49	67,319.96
GenCo5	43	443,949.43	477,337.27	562,530.47

Fig. 15. AMES table display (only partially shown): Daily GenCo profits, net earnings and revenues for the dynamic 5-bus test case with learning (days 42-43)

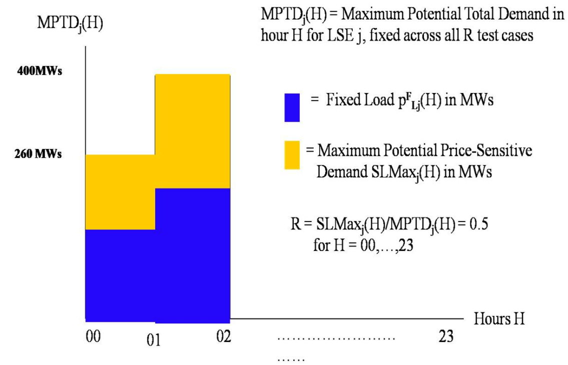

Fig. 16. Illustration of the construction of the R ratio for measuring relative demand-bid price sensitivity for the special case R=0.5

on the day-D supply offer choices of all other GenCos as well.

Intuitively, GenCos should have an increased ability to exercise "market power" (profitable control over prices) the greater the verticality of the LSE total demand curve. In particular, there is no natural upper bound on LMP levels when all LSE demand for power is fixed (price insensitive), implying a perfectly vertical total demand curve.

To test the sensitivity of LMPs to the degree of price-sensitive demand, we consider the ratio R of maximum potential price-sensitive demand to maximum potential total demand for each LSE j in each hour H of a typical day D. Specifically,

$$\mathrm{R}_j(H) \;=\; \frac{\mathrm{SLMax}_j(H)}{\mathrm{MPTD}_j(H)} \quad , \tag{13}$$

where SLMax_j(H) denotes LSE j's *maximum potential price-sensitive demand* in hour H as measured by the upper bound of its purchase capacity interval (2), and

$$\mathrm{MPTD}_j(H) \;=\; [\mathrm{p}^F_{Lj}(H) + \mathrm{SLMax}_j(H)] \tag{14}$$

denotes LSE j's *maximum potential total demand* in hour H as the sum of its fixed demand p^F_{Lj}(H) and its maximum potential price-sensitive demand SLMax_j(H) in hour H. See Fig. 16.

An increase in R for an LSE indicates an increased ability to exercise price resistance. Table I displays outcomes for an experiment involving three different R values for potential bid-in demand: R=0.0 (100% fixed); R=0.5 (50% fixed and 50% price-sensitive); and R=1.0 (100% price sensitive). For each tested R value, thirty runs were conducted with (13) maintained at the tested R value for each LSE j in each hour H.[6] As intuitively expected, average LMP levels, average total demand, average ISO operating costs, and average GenCo "market power" levels (as measured by the Lerner Index LI) all decrease monotonically with increases in R.

TABLE I
AVERAGE EFFECTS (WITH STANDARD DEVIATIONS) OF R CHANGES FOR THE DYNAMIC 5-BUS TEST CASE WITH LEARNING (DAY 100)

R	Avg LMP	Avg Total Demand	Avg Op Cost	Avg LI
0.0	70.10	318.21	9198.63	0.5692
	(3.14)	(0.00)	(125.88)	(0.01)
0.5	35.75	170.75	2717.73	0.4185
	(0.48)	(2.42)	(157.73)	(0.01)
1.0	23.23	108.51	1184.18	0.2078
	(0.48)	(5.80)	(125.88)	(0.01)

V. AMES TEACHING AND TRAINING CAPABILITIES

The release of AMES as free open source software (OSS) is meant to facilitate the use of AMES for teaching and training as well as for research. AMES permits economists to better understand the complicated physical constraints on power flow imposed by the transmission grid and engineers to better understand how incentives for strategic trading can have dramatic effects on resulting price and quantity outcomes.

The AMES homepage [2] has been designed for easy navigation. It includes pointers to software downloads, set-up information, manuals, tutorials, licensing information, and research applications.

An annotated pointer to the AMES homepage is included at a highly active resource site [15] specializing in OSS suitable for teaching and training about restructured electricity markets, as well as at the software site of the *IEEE Task Force on Open Source Software for Power Systems* [16]. In addition, AMES has been used as demonstration software in a power economics course catering jointly to engineers and economists; see [17].

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REFERENCES

[1] FERC, *Notice of White Paper*, U.S. Federal Energy Regulatory Commission, April 2003.
[2] L. Tesfatsion, *AMES Wholesale Power Market Test Bed Homepage*, hosted by the Economics Department, Iowa State University, www.econ.iastate.edu/tesfatsi/AMESMarketHome.htm
[3] J. Sun and L. Tesfatsion, "Dynamic testing of wholesale power market designs: An open-source agent-based framework," *Computational Economics*, Vol. 30, pp. 291–327, 2007. Working paper available: www.econ.iastate.edu/tesfatsi/DynTestAMES.JSLT.pdf
[4] J. Sun and L. Tesfatsion, "DC optimal power flow formulation and solution using QuadProgJ," *Proceedings*, IEEE Power and Energy Society General Meeting, Tampa, Florida, June 2007. Working paper available: www.econ.iastate.edu/tesfatsi/DC-OPF.JSLT.pdf
[5] H. Li, J. Sun, and L. Tesfatsion, "Dynamic LMP Reponse Under Alternative Price-Cap and Price-Sensitive Demand Scenarios," *Proceedings*, IEEE Power Engineering Society General Meeting, Pittsburgh, PA, July 2008. Working paper available: www.econ.iastate.edu/tesfatsi/DynamicLMPResponse.IEEEPES2008.LST.pdf
[6] H. Li and L. Tesfatsion, "Capacity Withholding in Restructured Wholesale Power Markets: An Agent-Based Test Bed Study," *Proceedings*, PSCE, Seattle, WA, March 2009, to appear. Working paper available: www.econ.iastate.edu/tesfatsi/CapacityWithholding.PSCE2009.LiTesfatsion.pdf
[7] A. Somani and L. Tesfatsion, "An Agent-Based Test Bed Study of Wholesale Power Market Performance Measures," *IEEE Computational Intelligence Magazine*, Vol. 3, No. 4, November, 2008, pp. 56–72. Working paper available: http://www.econ.iastate.edu/tesfatsi/AMESPerformanceMeasures.ASLT.IEEECIM2008.pdf
[8] MISO, *Homepage*, Midwest ISO, Inc., 2008. [Online]. Available: www.midwestiso.org/
[9] ISO-NE, *Homepage*, ISO New England, Inc., 2008. [Online]. Available: www.iso-ne.com/
[10] R. Baldick and W. Hogan,"Capacity constrained supply function equilibrium models of electricity markets: Stability, non-decreasing constraints, and function space iterations," Working Paper Series, Program on Workable Energy Regulation (POWER), University of California Energy Institute, Revised August 2002.
[11] H. Li, J. Sun, and L. Tesfatsion, "Separation and Volatility of Locational Marginal Prices in Restructured Wholesale Power Markets," Working Paper, Economics Department, Iowa State University, 2008.
[12] A. E. Roth and E. Ido, "Learning in extensive form games: Experimental data and simple dynamic models in the intermediate term," *Games and Econ. Behavior*, Vol. 8, pp. 164–212, 1995.
[13] I. Erev and A. E. Roth, "Predicting how people play games with unique mixed-strategy equilibria," *American Economic Review*, Vol. 88, pp. 848–881, 1998.
[14] M. Shahidehpour, H. Yamin, and Z. Li, *Market Operations in Electric Power Systems*. New York, NY: IEEE/Wiley-Interscience, John Wiley & Sons, Inc., 2002.
[15] L. Tesfatsion, *Open Source Software for Electricity Market Research, Teaching, and Training*, website hosted by the Economics Department, Iowa State University, www.econ.iastate.edu/tesfatsi/ElectricOSS.htm
[16] IEEE, *Task Force on Open Source Software for Power Systems*, ewh.ieee.org/cmte/psace/CAMS_taskforce/index.htm
[17] L. Tesfatsion, *EE/Econ 458: Restructuring of Wholesale Power Markets*, class website hosted by the Economics Department, Iowa State University, www.econ.iastate.edu/classes/econ458/tesfatsion/
[18] *Electric Energy Economics (E3) Group*, Iowa State University, Ames, Iowa, www.econ.iastate.edu/tesfatsi/E3GroupISU.htm

[6] More precisely, the three tested successively-increasing R values correspond to increases in the maximum potential price-sensitive hourly demand $\text{SLMax}_j(\text{H})$ for each LSE j in each hour H, with $\text{MPTD}_j(\text{H})$ as well as the ordinate and slope values for LSE j's price-sensitive demand bids in hour H held constant across runs to control for confounding effects. See Li et al. [11] for a detailed experimental design description together with a listing of the thirty numerical values used as random seeds for the thirty runs.

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